FEATURE EXTRACTION AND OPTIMIZATION OF REPRESENTATIVE-SLICE IN AMBIGUITY FUNCTION FOR MOVING RADAR EMITTER RECOGNITION

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ABSTRACT

Radar emitter recognition is an important and challenging subject in radar signal analysis and processing. In this work, an ambiguity function (AF) representative-slice based feature extraction and optimization algorithm is presented for unintentional modulation recognition of moving radar emitters. It considers near-zero slices of AF as representative feature set of radar emitters, which not only coincides with the characteristics of real radar signals, but also mitigates the computation problem and avoids undesired cross terms in existing AF based method. Direct Discriminant Ratio (DDR) criterion is further utilized to preserve the most discriminant features and boost recognition accuracy, by ranking the kernel points along the representative-slice. Experimental results validate the practical usefulness and high stability of the proposed approach on real data of moving radar emitters, as well as synthetic radar data from U.S. Naval Research Laboratory.

Index Terms—moving radar emitter recognition, feature optimization, unintentional modulation, ambiguity function, representative-slice

1. INTRODUCTION

Radar emitter recognition has attracted much attention in the last decade [1-5]. The goal is to identify a number of unknown specific emitters which are of same type and with same parameter. Generally, these approaches can be divided into two categories: intentional modulation recognition [1] and unintentional modulation recognition [2-5]. This paper focuses on the latter one, i.e., extraction and recognition of subtle but persistent features presented in these radar signals under unintentional modulation.

Ambiguity function (AF) was introduced to radar emitter recognition by Gillespie and Atlas in [2,3], where a class-dependent method was developed to optimize AF feature for classification and promising results have been achieved for simulation data from U.S. Naval Research Lab [6]. However, it is pointed out in this paper that there are still some drawbacks existed in this algorithm, such as:

1. This method has high computation burden and is sensitive to sampling data length, which makes such feature optimization infeasible for large scale data or in real time application.
2. It is designed for ideal or clean radar emitter signals. In practice, the received pulses often contain harmonic components or multipath components. So the global feature optimization in whole AF plane will be biased.
3. More importantly, it is unclear how this method deals with moving radar emitters, which is also rarely mentioned in available literature.

To overcome these limitations, an ambiguity function representative-slice based feature optimization algorithm is proposed in this paper. It efficiently extracts the near-zero slices of AF as intermediate feature set. Such scheme not only avoids “out of memory” problem as in whole-plane optimization, but also helps to identify individual moving radar emitters as well as static ones. Further, Direct Discriminant Ratio (DDR) criterion is used to rank and select the dominant kernel points along the obtained slices, which offers better kernel optimization performance in terms of “discriminant power” and feature sparsity, compared to DDR [2]. These advantages make the proposed method feasible in practical or real-time applications and scalable to large data sets, with improved recognition performance against the traditional methods.

2. CLASS-DEPENDENT KERNEL OPTIMIZATION FOR RADAR Emitter IDENTIFICATION

Gillespie and Atlas proposed to use a class-dependent method [2,3] to classify radar emitters. Ambiguity function is used to extract the initial features of radar signals, followed by a kernel optimization scheme in the obtained ambiguity function plane. With $\varphi = \varphi(\eta, \tau)$ being the kernel function and $\mathbf{A} = \mathbf{A}^{C} [\eta, \tau]$ being the “average” auto-ambiguity function of class $C$, class-dependant kernel is designed so as to find the optimal features in terms of classification accuracy,

$$\varphi_{C}^{\text{opt}} = \arg \max_{\varphi} \left\{ \sum_{\eta} \left[ \sum_{\tau} \left( \varphi \circ \mathbf{A}^{(i) \circ} - \varphi \circ \mathbf{A}^{(i) \circ} \right)^{2} \right] \right\},$$

where $\circ$ represents dot product.

It can be seen that the points in the auto-ambiguity function take the role of features, while the kernel takes the role of the weight. Accordingly, Fisher’s discriminant ratio (FDR) is used to rank the linear discriminant kernel points,

$$\text{FDR} [\eta, \tau] = \frac{\sum_{i=1}^{C} \mathbf{A}^{i} [\eta, \tau] - \mathbf{A}^{C} [\eta, \tau]}{\sum_{i=1}^{C} (\sigma^{C}) [\eta, \tau]}$$
where \( (\sigma^2)[\eta, \tau] = \frac{1}{J} \sum_{j=1}^{J} A_j^2[\eta, \tau] - \bar{A}^2[\eta, \tau] \) \( (3) \)

FDR is maximized when the separation between means of the classes is large and the within-class variance is small. After ranking the kernel points, the optimal number of nonzero points is determined by evaluating the classifier performance using the K best kernel points.

Unfortunately, such method has three limitations. First, it needs to rank all the kernel points in AF plane, which involves the calculation and store of \( N \times N \times N \) matrix. Here \( N \) represents the sampling data length. In practice, \( N \) is always large, which leads to high computation and even “out of memory” problem. Second, for a real radar pulse which contains harmonic or multipath components, the global optimization in whole AF plane will include the kernel points from cross terms. Moreover, it is unclear how to extend this method to moving emitter dataset, since it does not distinguish the features between “moving” and “static” emitters in theory.

3. RADAR EMITTER IDENTIFICATION VIA OPTIMIZING REPRESENTATIVE-SLICE

3.1. Representative-slice of ambiguity function

Fig.1 shows the ambiguity function of a real signal from a moving radar emitter under basic operation mode. It can be observed that the majority of AF is centralized along the axis of time delay. Due to the finite data length, the ambiguity function consistently decreases along the shift frequency axis and converges to zero rapidly. Since the energy of AF exhibits a peak at shift frequency being zero, the slices of ambiguity function with shift frequency near zero (including zero-slice) could be considered as the major representative feature sets of radar emitter pulse. Such feature approximation is straightforward, which not only coincides with the characteristics of real radar pulse, but also helps to decrease the computation complexity greatly.

For a moving radar emitter at a constant radial velocity \( v \), the distance between the passive receiver and detected emitter can be expressed as \( R(t) = R_0 - v; t \), where \( R_0 \) is the initial distance at \( t = 0 \). Since the relative velocity is far less than \( c \), the velocity of electromagnetic wave, the receiver delay can be written as,

\[
\tau = \frac{R(t)}{c - v} \approx \frac{1}{c} (R_0 - v; t) \quad (4)
\]

The phase difference between the received signal and original emitter signal is calculated as follows,

\[
\varphi = -\alpha_0 \tau = -\frac{1}{c} (R_0 - v; t) \quad (5)
\]

where \( \alpha_0 \) is the angular frequency of emitter signal. The resulting Doppler frequency of moving emitter can be deduced as follows,

\[
f_d = \frac{1}{2\pi} \frac{d\varphi}{dt} = \frac{\alpha_0}{2\pi} \frac{v}{c} = f_0 \frac{v}{c} \quad (6)
\]

It is obvious that such Doppler frequency is a constant pretty close to zero and is far less than central frequency \( f_0 \), which makes the choice of representative-slices (including zero-slice) more reasonable. Besides, in modern electronic warfare, we often get few emitter pulses, within which the accumulated Doppler frequency caused by the relative motion is negligible for a receiver. Broadly speaking, the average Doppler frequency could be also relaxed as a near-zero constant even when the emitter is with varying velocity. It should be noted there also exists two small symmetrical energy distributions far away from near-zero slices in the AF plane. Such cross terms might be caused by the harmonic components or multipath components in received signals, which are common for real emitter data. It also indicates that the exclusion of cross terms will benefit the subsequent feature optimization around the auto terms, in order to obtain robust and stable features of radar emitter.

3.2. Feature ranking using DDR criterion

Once the representative-slice of ambiguity function is obtained, we could further select the most discriminant kernel points using certain objective function. However, from the point of view of each variable dimension, the class variance is quite close to each other, due to the similarities of the received radar emitter signals. According to (3), the calculation of each class variance will be sensitive to the “noisy points” or “outliers”, resulting in an unstable FDR curve. Here we proposed to use Direct Discriminant Ratio (DDR) as an alternative criterion to rank the kernel points,

\[
{\text{DDR}}[\eta, \tau] = \frac{1}{J} \sum_{j=1}^{J} \left[ A_j^2[\eta, \tau] - \bar{A}^2[\eta, \tau] \right]^{1/2} \quad (7)
\]

We still use the term “ratio” since the variance could be treated as a constant. Shift frequency \( \eta \) is set to an integer near zero so as to rank the points along the major direction of ambiguity function distribution. If a large range of \( \eta \) is involved, such criterion could be employed to optimize the kernel function in whole AF plane. DDR offers well kernel optimization in terms of minimum mean-squared-error, and tends to produce sparse solution to kernel design, as can be seen in the next section.

3.3. Summary of the proposed algorithm

Similar to the class-dependent method in [2,3], our proposed algorithm evaluates the classification performance
using the $K$ best kernel points and selects $K_{\text{opt}}$ points with the greatest probability of correct classification. Subsequent classifiers could be user defined. The whole algorithm is summarized as follows:

**Algorithm 1:** Representative-slice feature optimization  

**Step 1. Pre-processing**  
Radar pulses are demeaned and normalized to a standard deviation of one.

**Step 2. Feature extraction**  

a) The input signals are transformed into ambiguity function plane to get an initial time-frequency representation.

b) The representative slices are extracted to get an intermediate feature set.

c) Rank and select the best kernel points along these representative slices of AF by DDR. Construct the optimal kernel by evaluating the best recognition performance.

**Step 3. Classification**  
With the chosen $K_{\text{opt}}$ kernel points, classification is performed on the test data.

4. EXPERIMENTAL RESULTS

4.1. For simulation data of static radar emitter

In the first experiment, we use the synthetic emitter data released by U.S. Naval Research Lab [6], which could be treated as a kind of ideal data from static emitters. We empirically compare four feature extraction methods, i.e., the proposed ambiguity function (AF) representative-slice based feature optimization, zero-slice based method (as a special case), power spectrum estimation (PSD), and power spectrum estimation based on 4th order AR model. Nearest Neighbor classifier is used in the classification stage for its simplicity. The recognition rate versus train numbers is shown in Fig.2. All the results are averaged by 50 runs.

![Fig.2.](image)

**Fig.2.** Recognition rate versus train number for synthetic data.

It can be seen that the proposed AF representative-slice based feature optimization method achieves almost 100% accuracy even when the training set is small or incomplete, and consistently outperforms the other three methods.

Surprisingly, although zero-slice is designed specifically for static emitter data, the proposed representative-slice based feature optimization is more robust, which may be due to the fact that near-zero slices contain more potential discriminant information than zero-slice.

We should note that, although the class-dependent kernel optimization algorithm in [2,3] can achieve the same performance as our method (its performance curve is omitted), such whole plane optimization is only feasible for ideal radar data with short length or low sampling rate. Besides, the FDR based kernel points ranking is sensitive to the estimation of each class variance. As shown in Fig.3, the ranking curve of FDR converges slowly and more kernel points tend to be selected compared to the DDR criterion.

4.2. For real data of moving radar emitter

In this experiment, we focus on real moving emitter data which contains 270 radar pulses from nine transmitters being of same type and with same parameter. Each pulse is collected with 800 sampling points. We randomly select 20 pulses per class for training and the remaining 10 pulses are used for testing. Support vector machine (SVM) and Nearest Neighbor (NN) algorithm are used as the classifiers respectively. The average recognition rate of 20 runs by each method is summarized in Table 1. We report the best recognition rate of our method by performing 5 individual near-zero slices based feature optimization.

It is worthwhile to highlight several aspects of the proposed approach on real radar emitter experiment:

1) Our algorithm performs the best, compared with traditional power spectrum estimation (PSD) method, 4th order AR model based method, and zero-slice based one, no matter what kind of classifier is employed.

2) The class-dependent method in [2,3] is not applicable since the sampling points are relatively large for feature optimization in whole AF plane, resulting in the calculation and the store of higher order matrix infeasible.

3) Comparable recognition result can be obtained by both classifiers. It indicates the effectiveness of the DDR optimization criterion, which helps to preserve the most discriminant kernel points and produce a compact feature subset for class separation.

4) More interestingly, the representative-slice based method yields higher accuracy than zero-slice based one, which validates the usefulness of near-zero slices over zero-slice especially for moving emitter data.

Further, we evaluate the performance of kernel point ranking in representative-slice using DDR. Fig. 4 shows the correct classification rates versus the number of selected kernel points using SVM as classifier. We can observe that with the increasing number of selected kernel points, our method can approach its best recognition rate rapidly. Thus, only a small part of kernel points (typically less than 1/5 of total sampling points) are needed to construct the optimal feature vector.

Finally, we empirically compare the recognition rate based on different representative slices directly using SVM classifier, without further DDR kernel points ranking. It can be seen from Fig.5 that a slightly higher correct rate is...
reached by zero plus 2 slice, compared to zero slice. It confirms the analysis in section 3.1 that tiny Doppler frequency caused by moving radar emitter is more crucial for moving emitter recognition in practice. Although the fusion recognition [5] with limited near-zero slices is a feasible solution to improve the performance, how to select the optimal slice is still an open question.

5. CONCLUSIONS

In this paper we have presented a novel feature optimization framework for moving radar emitter recognition. Our contribution is three-fold: First, we adopt the near-zero slices instead of whole AF function as representative feature set, which avoids feature weight on undesired cross terms caused by harmonic or multipath components in practice. Second, theoretical justification as well as experimental results show that representative slice based method is more suitable for moving emitter identification, which also cast zero-slice based method as a special case. Finally, DDR is suggested in this framework to boost recognition accuracy and offer significant feature reduction. Comparisons to most used techniques have shown the superiority of the proposed approach, which is scalable to large data set and potential for practical applications.

6. REFERENCES


